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# Pixel-wise Motion Detection in Persistent Aerial Video Surveillance

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Analysis

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# **Pixel-wise Motion Detection in Persistent Aerial Video Surveillance**

- **Motivation**
- **Method**
- **Phase congruency**
- **Decomposition/analysis**
- **Motion metric**
- **Precession results**
- **Independent movers results**



# Motivation

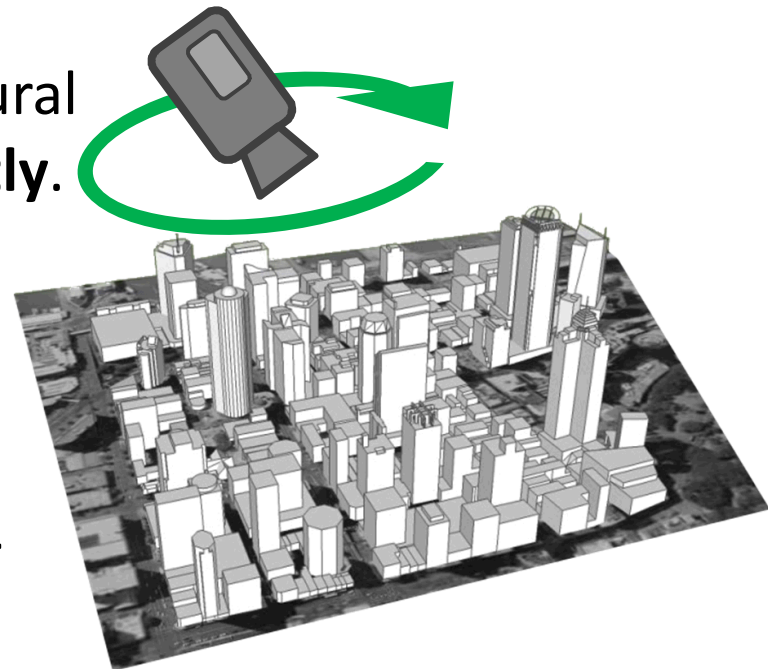
In ground stabilized WAMI, stable objects with depth appear to have precessive motion due to sensor movement alongside objects undergoing true, independent motion in the scene.

## Computational objective

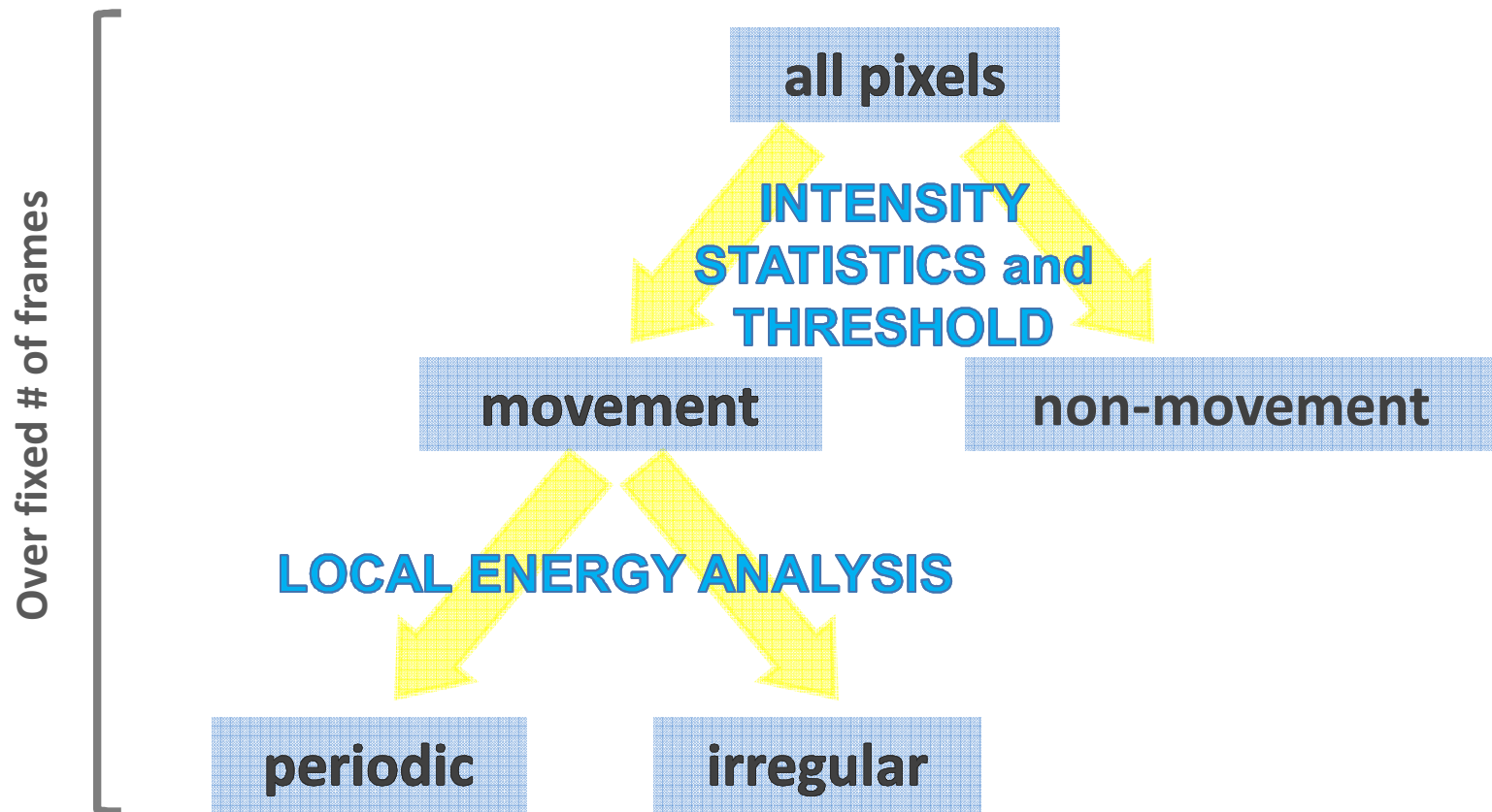
Disambiguate independent and structural motion in WAMI **efficiently** and **robustly**.

## Applications

- Increase video compression rate via object-oriented video compression
- Robustly identify moving objects for end users in sparse terrain

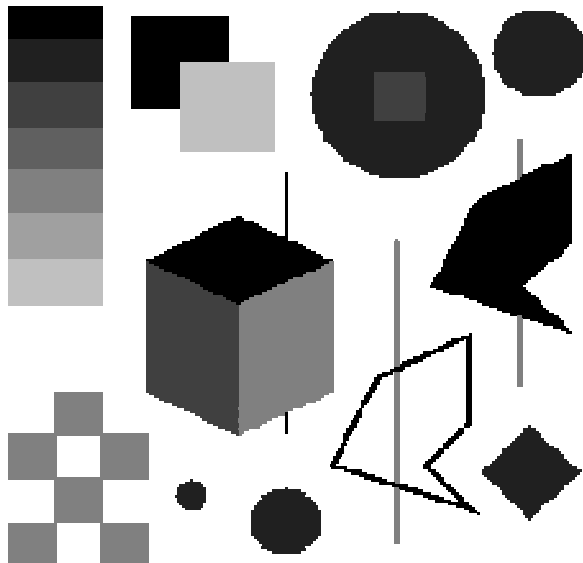


# Method

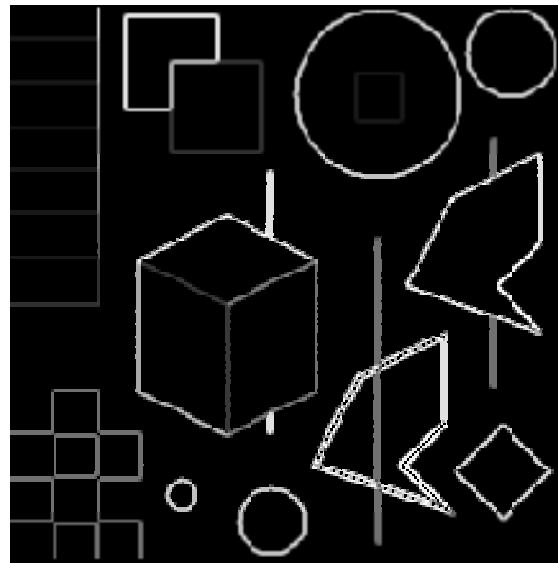


# Phase congruency

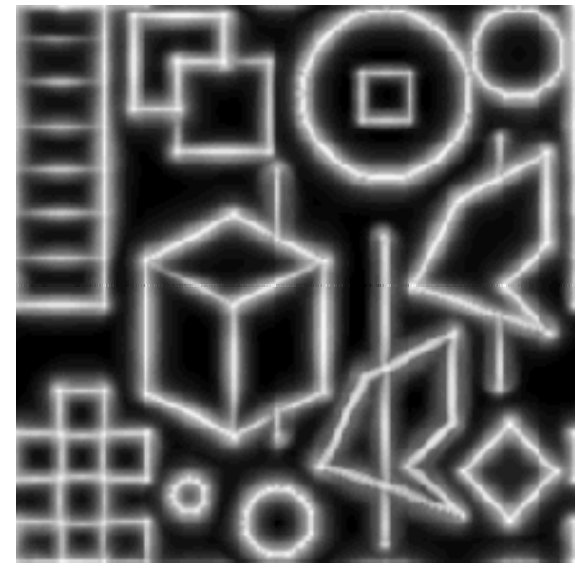
2D application in computer vision



original



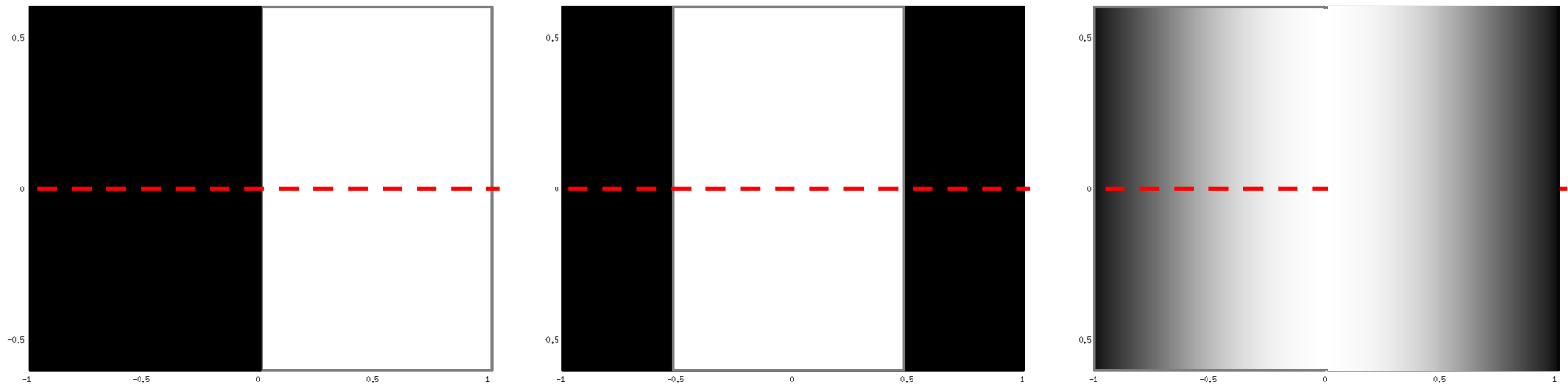
Canny



phase congruency

# Phase congruency

Frequency components in same phase





# Analytical (de)composition

$$\begin{aligned} f &= f_s \odot f_e \\ &= f_s \cdot f_e - \tilde{f}_s \cdot \tilde{f}_e \end{aligned}$$

$f_e$  = smooth energy

$f_s$  = local energy

$\tilde{f}$  = Hilbert transform of  $f$

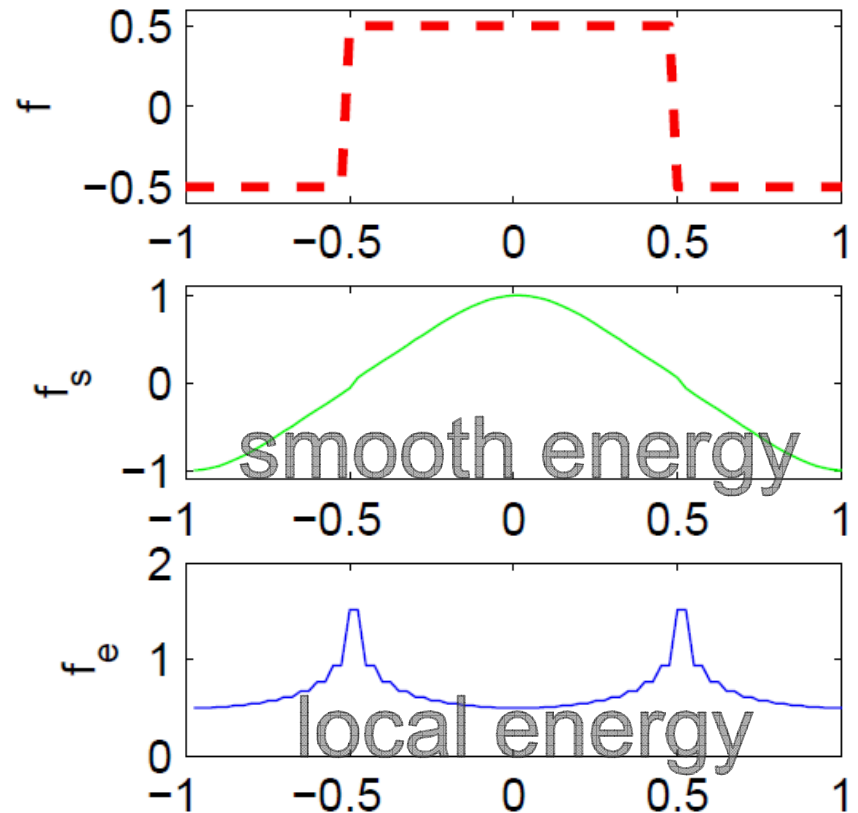
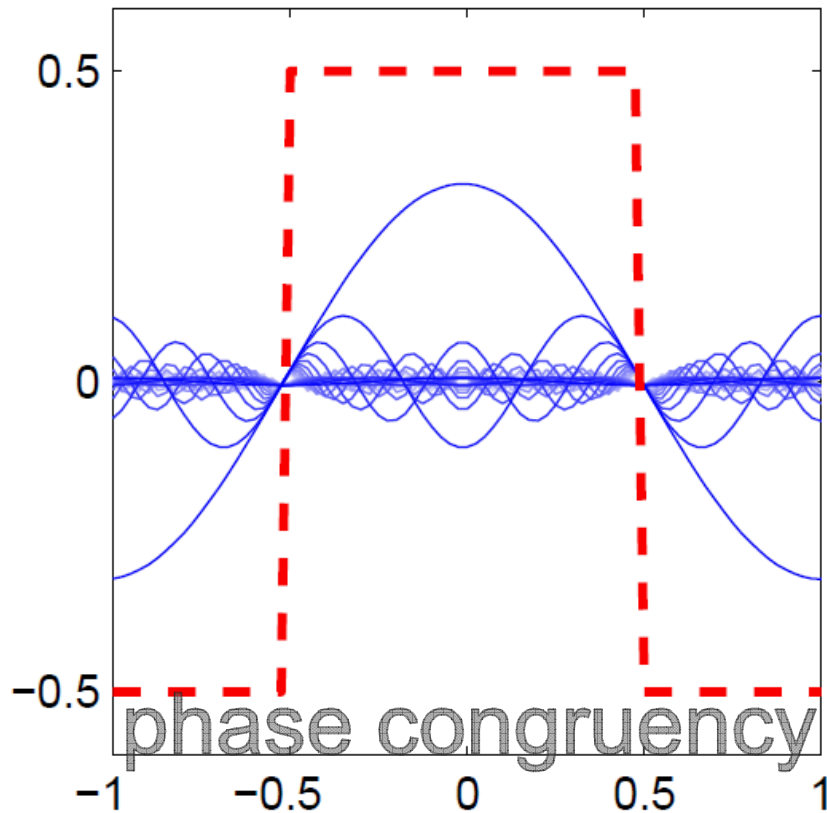
$$f_e = \sqrt{f^2 + \tilde{f}^2}$$

$$\begin{aligned} f_s &= f \oslash f_e \\ &= \frac{f \cdot f_e + \tilde{f} \cdot \tilde{f}_e}{f_e^2 + \tilde{f}_e^2} \end{aligned}$$

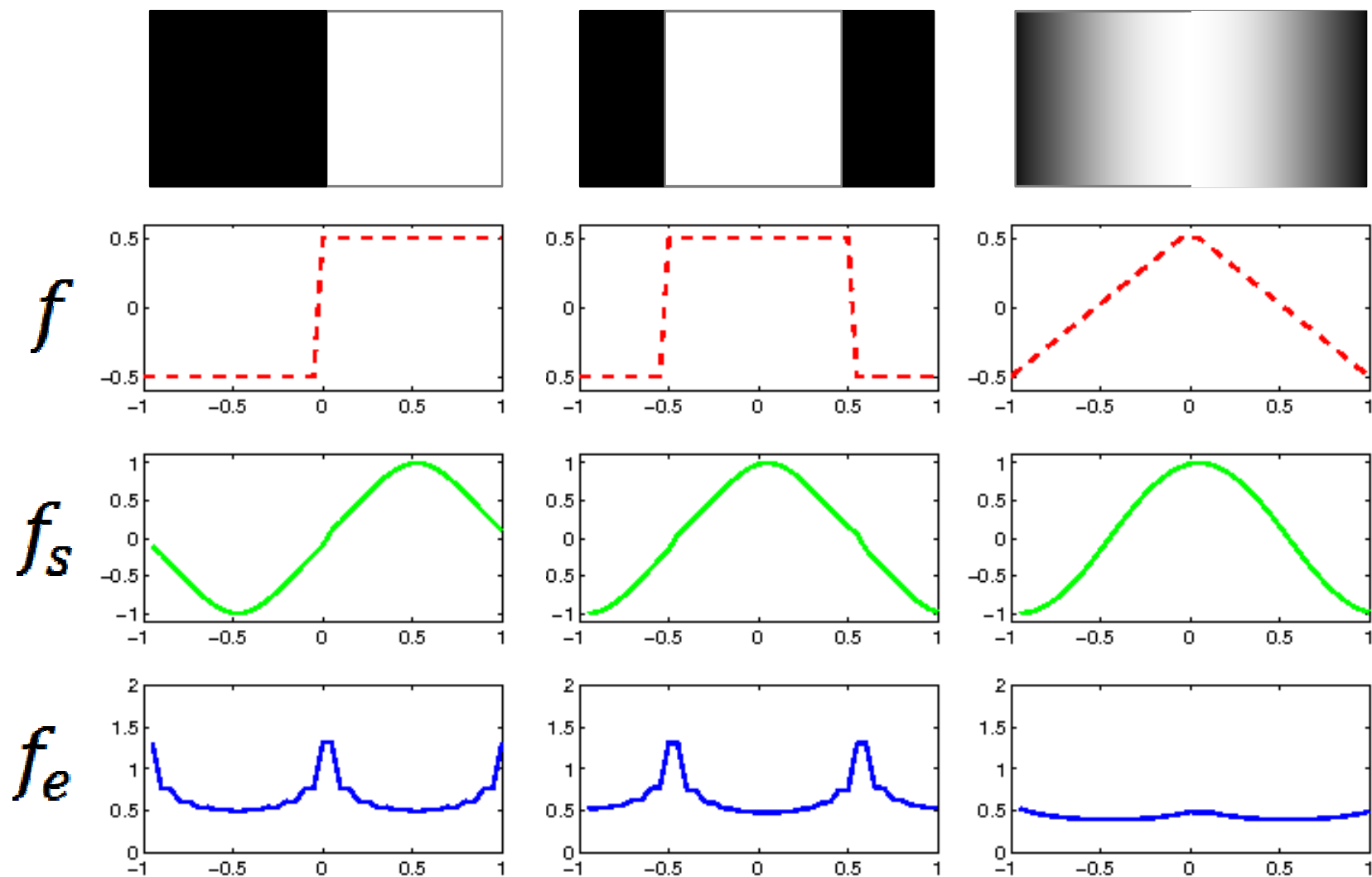
$$f_e(x) \propto PC(x)$$

R.A. Owens. **Feature free images**. Pattern Recognition Letters, 15 (1994), pp. 35–44.

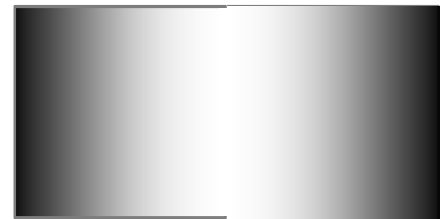
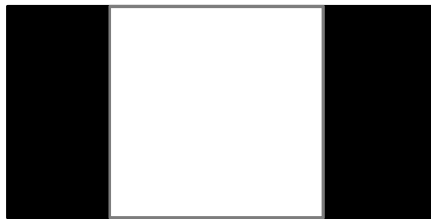
# Decomposition



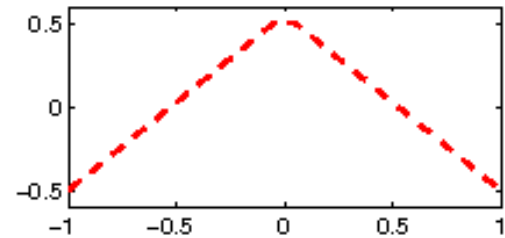
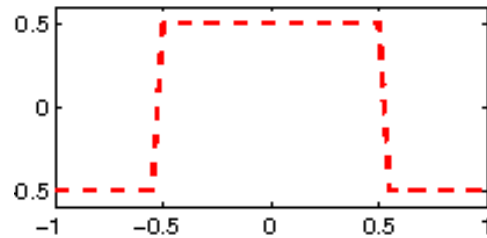
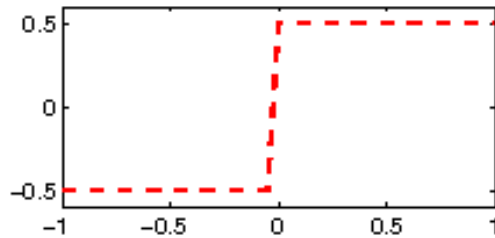
# Decomposition



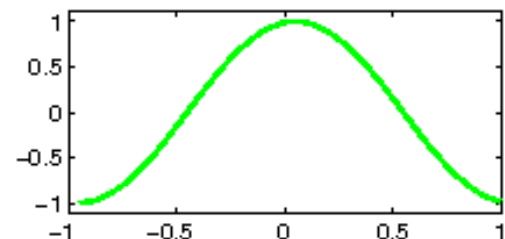
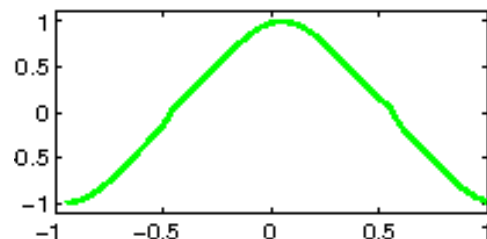
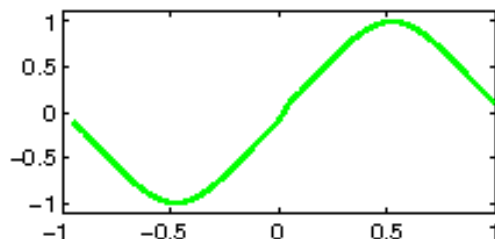
# Decomposition



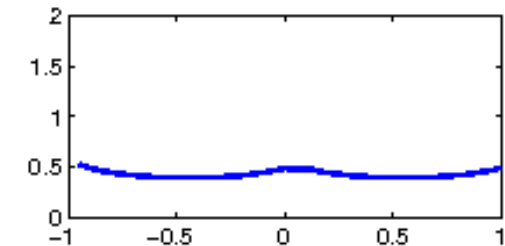
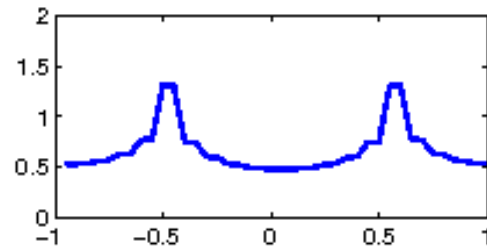
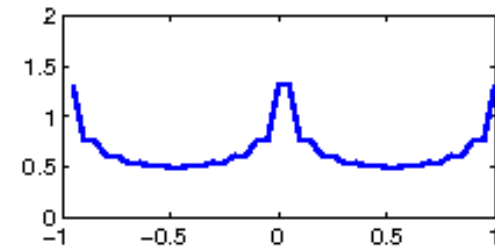
$f$



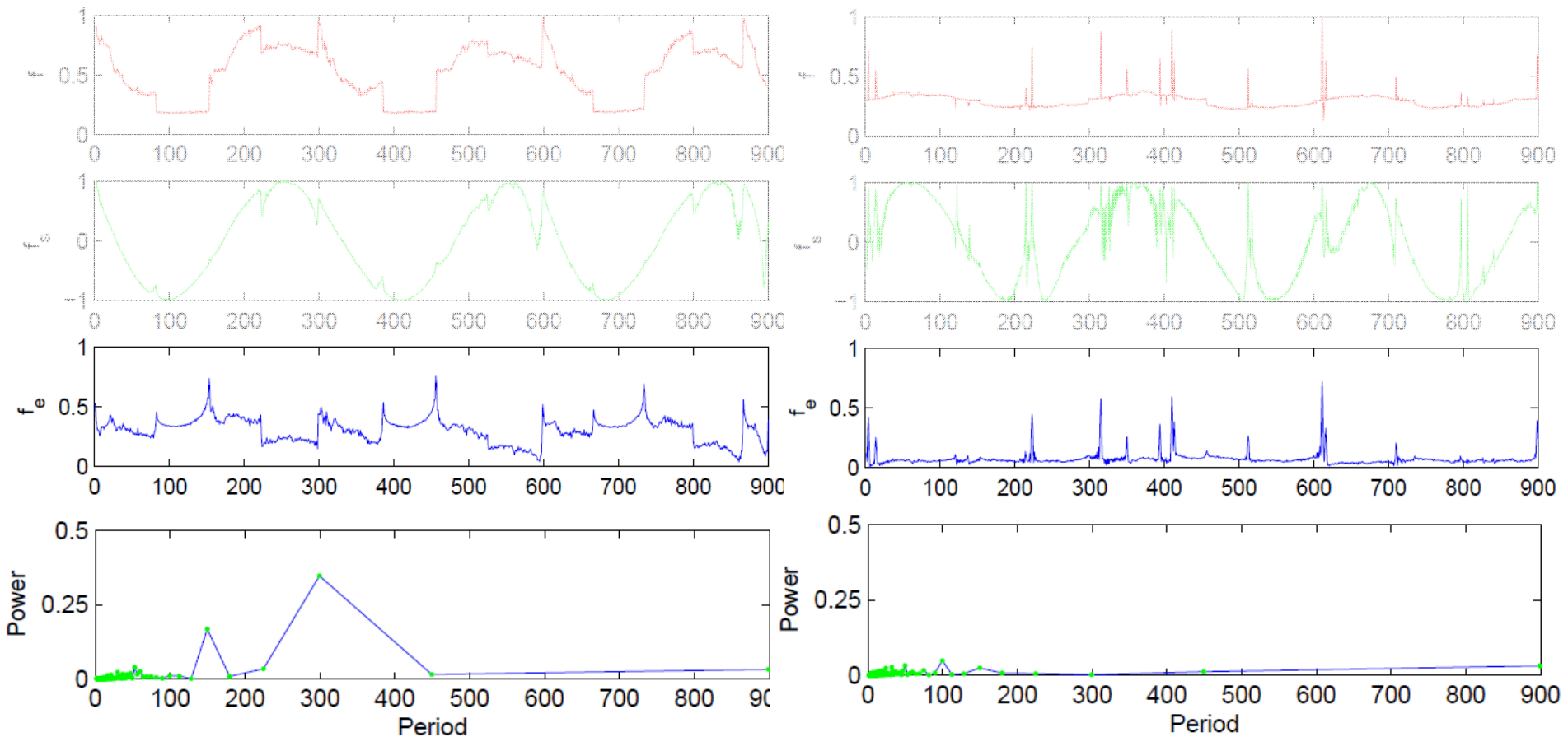
smooth  
energy



local  
energy



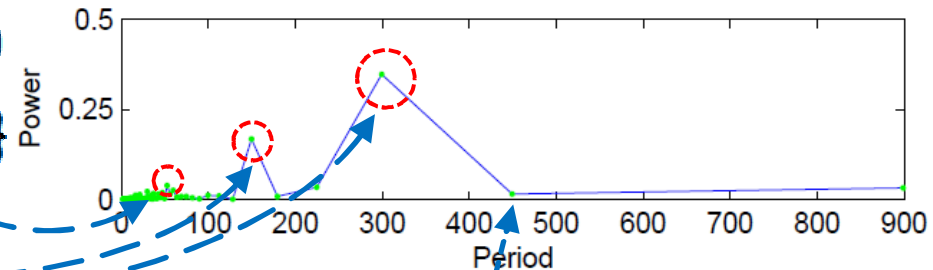
# Time-frequency analysis



# Periodicity metric

Period power spectrum for  $f_e(\mathbf{x})$

Let  $\mathcal{P} = \{p_1(\mathbf{x}), p_2(\mathbf{x}), \dots, p_\tau(\mathbf{x})\}$



Motion metric

$$g(\mathbf{x}) = \sum_{i=1}^{\boxed{k}} p_i(\mathbf{x}), \quad k \leq \tau \quad \tau < \boxed{n/2}$$

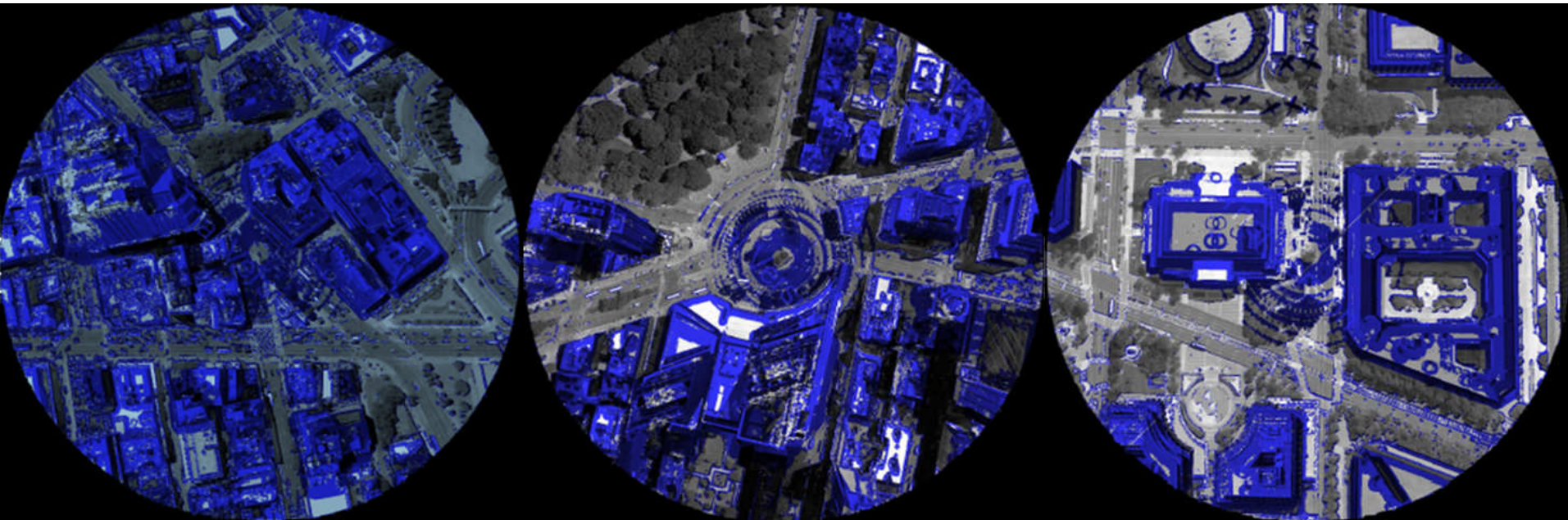


# Periodic motion





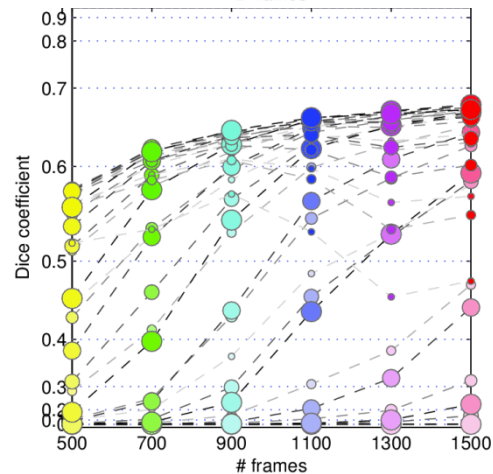
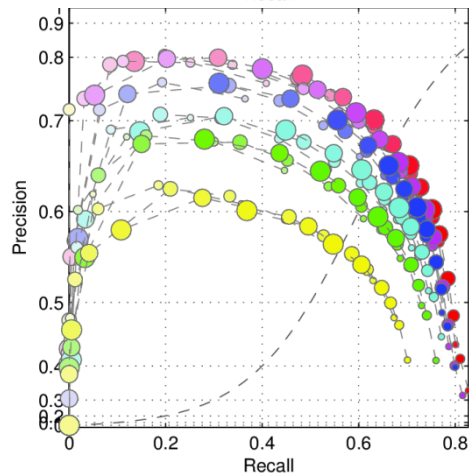
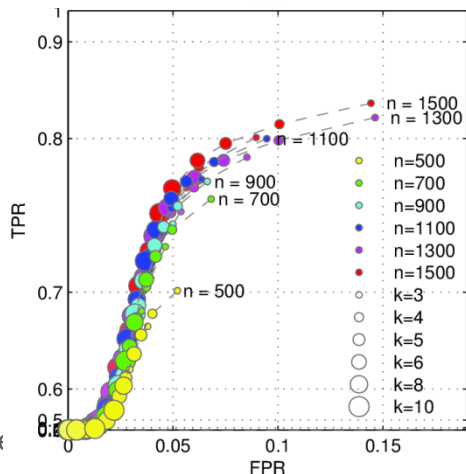
# Periodic motion



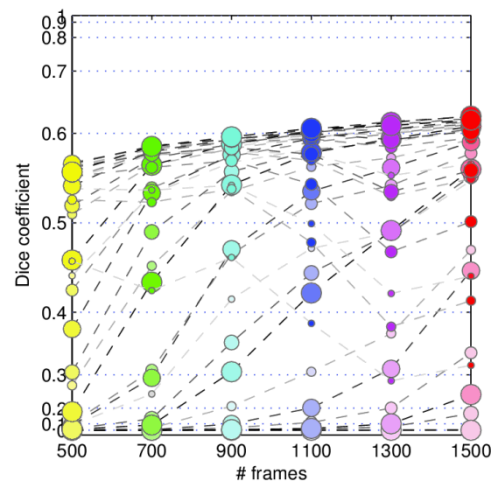
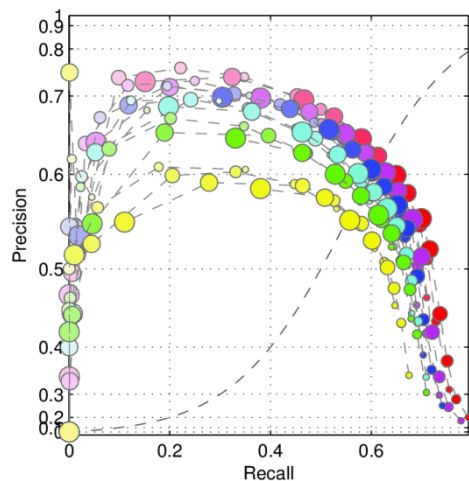
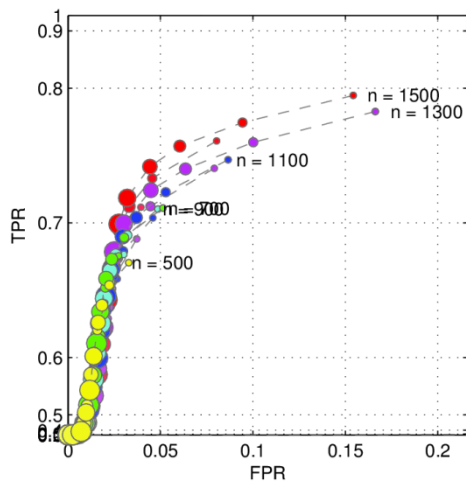


# Independent motion

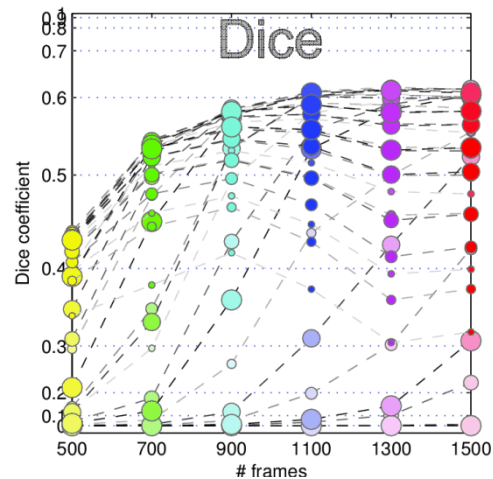
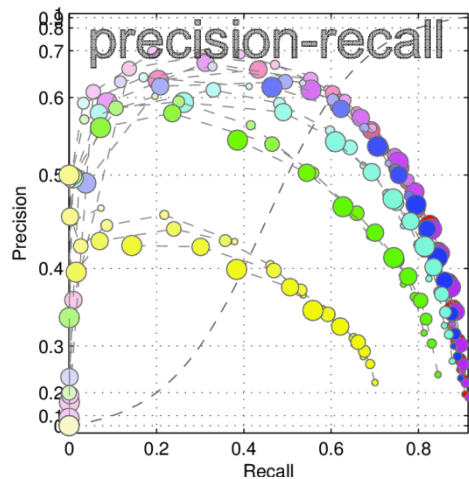
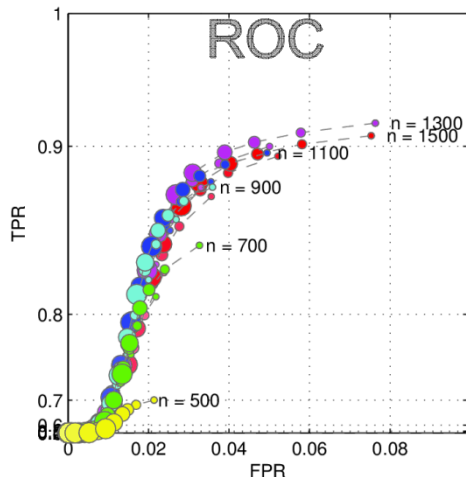
Block 3



Block 2



Block 1



# Conclusions

- Devise motion metric based on periodicity of intensities
  - Sensitivity analysis shows balance between  $\alpha$  and  $\beta$  will give most optimal results
  - Most optimal is 2-3 cycles of precession